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Fleet monitoring for distributed energy systems

分布式能源系统的车队监测

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Abstract – **Distributed energy systems such as wind turbines or tidal power systems share the properties of (1) having a rising number of similar installed system setups, (2) being installed mostly in remote areas with limited access and (3) needing a high system reliability. This makes fault diagnosis and identification (FDI) a crucial but challenging part for operation and maintenance (O&M) of these systems. This paper will focus on a method to use condition information of equal components in different machines and under different working conditions, to extract useful information for FDI of those components. A definition for fleet monitoring for FDI will be introduced. It will be shown that by extracting specific features of the components condition information and by combining these features from different machines, additional FDI information can be gained. Therefore, the focus of data analysis is the fleet information and less only individual systems information. It will be shown that properties of the introduced method can resolve common FDI drawbacks, e.g. setting up alarm thresholds. The method is based on the calculation of selected features from each system in a high dimensional common feature space. The main advantage is the absence of absolute measures for FDI and use of relative measures between components/machines in the fleet. Besides the theoretical approaches, an example using temperature and vibration data of 17 bearings test runs (PRONOSTIA data set) will be given. The runs of the bearings were performed with different speed and load and were only stopped by significant degradation. The purpose of the paper is to increase system reliability by using fleet information and, therefore, provide additional information for FDI.**

Keywords – **Fleet Monitoring, Condition Monitoring, Energy Systems. Bearing, Multivariate normal distribution**

I. Introduction

Worldwide an increasing demand for energy can be observed. More than 80 % of global energy, which is generated from renewable source, is hydro power. In addition to that the annual increase is approximately 3 %. There are considerable opportunities for hydroelectric plants, since only one fifth of technical feasible potential of hydro power has been deployed. North America utilized the biggest potential of hydro power, approximately 33 %, followed by Europe including the CIS 30 %, Australia 27 %, Asia 23 % and finally Africa with the lowest percentage of 8 %. [1] [2]

Mostly distinction is made between run-of-the-river power plant, storage power plant, pumped storage hydro power station and tidal power plant. The run-of-the-river power plant uses the flow of the river to generate electricity and also low drop height is characteristic. Storage power plants certainly have a high gradient and use the storage capacity of dams to generate electricity. A big advantage of storage power plants is that they are both used to cover the electrical base load and peak-load operation. The pumped storage power plant also offers the capability to pump the water into a catch basin. To allow this, the energy, which is available when demand is low, is used for example at night. At peak times, electricity can be feed in again. The tidal power plant converts the potential and kinetic energy from the tides of the sea into electricity. They are built in bays and estuaries, which have a particularly high tide.

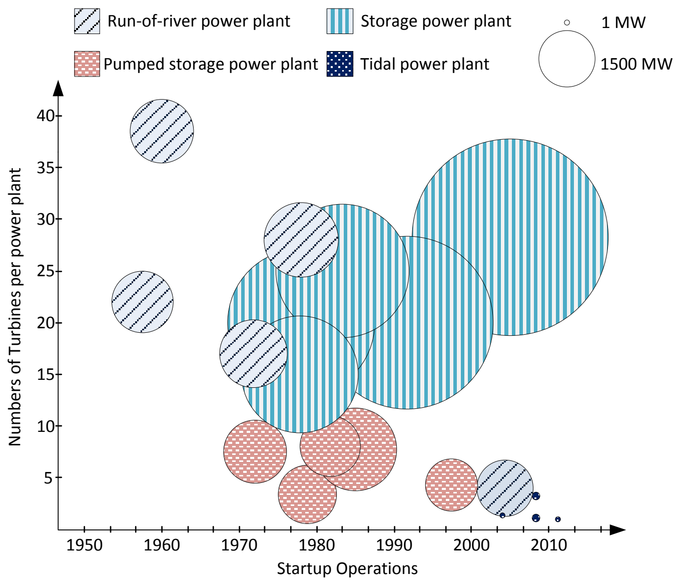

Fig. 1, Selection of hydro power plants.

Fig. 1 and Table 1 show the different types of hydroelectric plants. For each type the world's largest power plants are listed. Furthermore the diagram shows when the hydro power plants were put into operation and how many turbines were installed. The bigger the circles, the more total power output the individual power plants have. It is particularly interesting to note that tidal power stations are typically equipped with rolling bearings, in contrast to the other types of power plants, which have almost exclusively plain bearings. Tidal energy systems are similar to all distributed energy systems such as on- and offshore wind turbines, communal power stations, waste-to-energy power stations and others. Distributed power system combine the following properties relevant for O&M: (1) having a rising number of similar installed system setups, (2) being installed mostly in remote areas with limited access and (3) needing high system reliability.

Using the introduced example of water power plants shown in Fig. 1 in all major power plants the turbines are concentrated in one place even in one machine hall. Therefore the mentioned O&M properties do not apply. By looking at the tidal power plants and referring to the defined O&M properties: (1) tidal power plants are installed in clusters of similar machines and run under similar stream/tidal conditions, (2) each turbine is located separately underwater and therefore requires increased effort to be accessed and (3) are designed to run without onsite support for 6 months [3].

TABLE 1: SELECTION OF HYDRO POWER PLANTS.

Name of power plant	Country	Startup Operation	Numbers of turbines per power plant	Total power output [MW]
Run-of-river-power plant				
Chief Joseph Dam	USA	1979	27	2620
John Day Dam	USA	1971	16	2160
Beauharnois Hydroelectric Power Station	Canada	1961	38	1903
The Dalles Dam	USA	1957	22	1.780
Nathpa Jhakri Dam	India	2004	6	1.500
Pumped storage power plant				
Bath County	USA	1985	6	3.003
Ludington	USA	1973	6	1.872
Dinorwig	Great Britain	1984	6	1.728
Racoon-Mountain	USA	1978	4	1.600
Shin-Takasegawa	Japan	1998	4	1.280
Storage power plant				
Three Gorges Dam	China	2006	26	18.200
Itaipú	Paraguay and Brazil	1991	20	14.000
Guri	Venezuel a	1978	20	10.235
Tucuruí	Brazil	1984	25	8.370
Sayano-Shushens kaya Dam	Russia	1978	8	6.400
Tidal power plant				
RTT 2000	Wales	2011	1	2
SeaGen	UK	2008	2	1.5
OCT	Scotland	2008	1	1.5
TidEl	Cumbria	2005	2	1

By knowing these challenging properties most of the distributed energy systems are equipped with remote condition monitoring systems measuring e.g. vibration to estimate the condition of the system and sending the data to a centralized control center. At those centers the data is analyzed and O&M measures are decided.

The purpose of the paper is to increase system reliability by using fleet information and, therefore, provide additional information for O&M. First the problem of fleet monitoring will be introduced (II), then the proposed method is described (III) and later demonstrated using bearing data (IV).

II. Problem Definition

The problem that is researched in this paper is defined as supporting the monitoring effort of distributed energy system based on existing machine data. The focus is to detect unusual machine behavior.

For this purpose the authors define the term fleet monitoring as: *Monitoring a fleet of similar type or identical machines, operating under similar conditions, to detect unusual machine behavior of a single machine if compared to the fleet.* Additionally the introduced fleet monitoring method makes no use of design specific quantitative thresholds and no use of historical monitoring data. The focus is not on machine individual FDI or prognosis of future machine conditions.

III. Theoretical Approach

The method of fleet monitoring is presented with the focus on roller bearings and assumes that acceleration over time data of a machine fleet is available.

Features

At first k features of m separate bearings B_m of m machines of the machine fleet for n time intervals (of equal length) are extracted (Fig. 2) resulting in values defined as $f_{k,n,m}$. In this paper the root mean square (RMS), the peak magnitude to RMS ratio (Peak2RMS) and the maximum to minimum difference (Peak2Peak) are used [4].

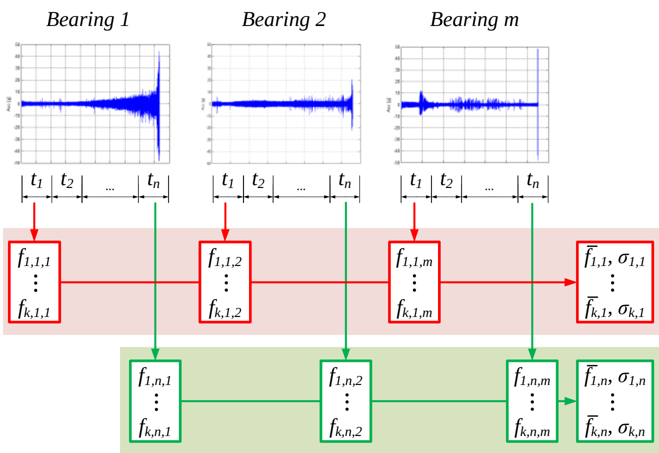

Fig. 2, Feature extraction method.

Test of normal distribution

For each time interval n all extracted features $f_{k,n,m}$ are tested if the features in that specific time interval are normal distributed. Therefore the Anderson–Darling test with a significant level of 5 % is used. This test was chosen because of its capability to test a small sample size. The test is valid until a sample size of at least *8*. Therefore a machine fleet of less than *8* machines cannot be assumed normal distributed and therefore not monitored with the method of this paper. [5]

Only if all features k are normal distributed for a specific time interval n, their mean values $\bar{f}_{k,n}$ (Eq. 1) and their standard deviations $\sigma_{k,n}$ (Eq. 2) are calculated.

$$\bar{f}_{k,n} = \frac{1}{m}\sum_{i=1}^{m} f_{k,n,i} \quad (1)$$

$$\sigma_{k,n} = \sqrt{\frac{1}{m}\sum_{i=1}^{m}\left(f_{k,n,i} - \bar{f}_{k,n}\right)^2} \quad (2)$$

Multivariate normal distribution

The core method for fleet monitoring is the multivariate normal distribution (also called multivariate Gaussian distribution). It is a multi-dimensional type of univariate normal distributions. Fig. 3 illustrates an example of a two-dimensional normal distribution for a specific time interval n. The abscissa and ordinate axis display two different features (f_1, f_2), their mean values ($\bar{f}_{1,n}$, $\bar{f}_{2,n}$) and their standard deviations ($\sigma_{1,n}$, $\sigma_{2,n}$) as characteristic values for a standard normal distribution. It is important to note that the representation is valid for only a single time interval. Another time interval is checked separately from all other time intervals. [6]

If the criterion on normal distribution of every feature is fulfilled, the original values of every dataset are compared to the statistically calculated multidimensional values $\bar{f}_{k,n}$ and $\sigma_{l,n}$. The calculated (double) standard deviations of each feature are then used as thresholds ($2\cdot\sigma_{k,n}$) which equals *95.45 %* of the distribution. The features $f_{k,n,m}$ of each bearing B_m are then compared to the $2\cdot\sigma_{k,n}$ threshold of the specific time interval n. If all $f_{k,n,m}$ of each bearing B_m are not within this range of tolerance, the bearing could be classified as a bearing with unusual behavior.

In Fig. 3 an example with just two features, f_1 and f_2, and $m=8$ Bearings for specific time interval is given. It can be seen that the bearings B_1 to B_4 are all within the tolerated range of all features. In contrast, bearings B_5 and B_6 are neither within the tolerated range of f_1 nor f_2 indicating that these bearings might have a unusual behavior. Nevertheless, bearings B_7 and B_8 are not within the tolerance of single features. Bearing B_7 is only within the tolerated range of f_2 and bearing B_8 is only within the tolerated range of f_1. Therefore, both bearings are classified as having usual behavior.

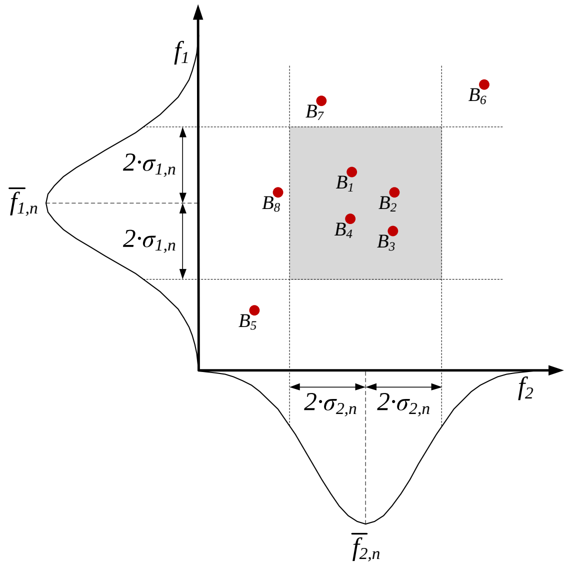

Fig. 3, Two-dimensional normal distribution for time interval n.

IV. Application

Data description

For the multivariate analysis of the above described features, an already existing dataset was used. The dataset descends from the FEMTO-ST Institute (Besançon, France) which has done experiments on their laboratory experimental platform named PRONOSTIA for a bearings' life duration prognostic challenge called "IEEE PHM 2012 Data Challenge" (in the following referred to as Challenge) [7]. The objective of the laboratory platform is to provide real experimental datasets in a short time. The data describes failures of ball bearings during their different operating times.

The published datasets of the Challenge represent three different load cases. Within the first load case, in total seven bearings were damaged at *1,800 rpm* and a force of *4.0 kN*. Additionally, seven bearings were provoked to reach failure at *1,650 rpm* and *4.2 kN*. The last load stage was *1,500 rpm* and *5.0 kN*. Three bearings were experimentally tested under this determined condition. The test was stopped when the amplitude of the bearing vibration signal exceeded *20 g*.
During the experiments, a tenth of a second of horizontal and vertical vibration signals were recorded each *10* seconds at a sample frequency of *25.6 kHz*. The first trial of fleet monitoring for these bearings is based on the features of the horizontal vibration signal because the load was applied in horizontal direction. The previously described features of the horizontal vibration signal of *17* bearing datasets were analyzed within this paper.

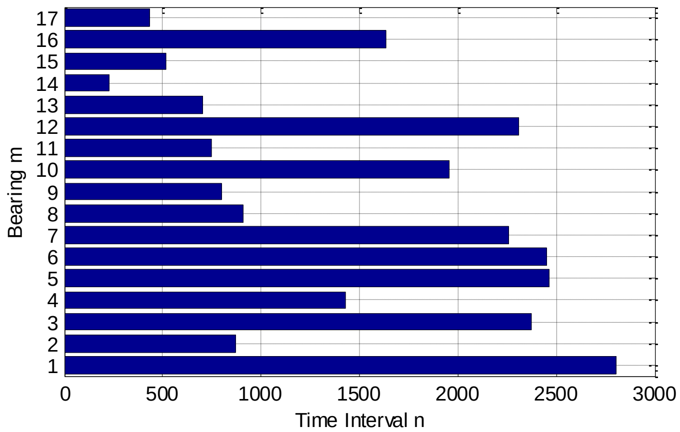

Fig. 4, Available time intervals n for all 17 bearings.

Results

The available time intervals n for each bearing m is shown in Fig. 4. Because of a minimum of at least 8 required bearings, to assure test for normal distribution, the method will not deliver a result after the end of the life time of bearing $m=16$ at time interval $n=1637$. It has to be noted that always all bearings m are tested of each time interval n, assuming that all bearings started operating at $n=1$.

The method is implemented as described in section III and was tested with the introduced data set. Fig. 5, 6, 7 and 8 shows the result of 4 selected bearings for a three dimensional normal distribution. The normal distributed features (RMS, Peak2RMS and Peak2Peak) over time intervals are plotted for the bearings $m=4, 9, 16$ and 17. The ordinate axis represents the ratio defined in Eq. (3):

$$ratio_{k,n,m} = \frac{|f_{k,n,m} - \bar{f}_{k,n}|}{\sigma_{k,n}}. \quad (3)$$

Also marked is the $2{\cdot}\sigma_{k,n}$ threshold. If two features exceed this threshold in the same time interval an unusual behavior is detected. The results of all 17 bearings are summarized in Table 2. It has to be noted that the grey marked bearings are the ones where the criteria of at least 8 bearings in the fleet is not fulfilled anymore therefore the method of this paper cannot be applied. This is due to the fact that always the same n of all bearings is compared and that each bearing has an individual life span. Therefore a bearing that is considered damaged by [7] does not have any further measurements and falls out of the fleet. Additionally Table 2 shows in percentage when the unusual behavior was detected as a fraction of the total number of measured time intervals n.

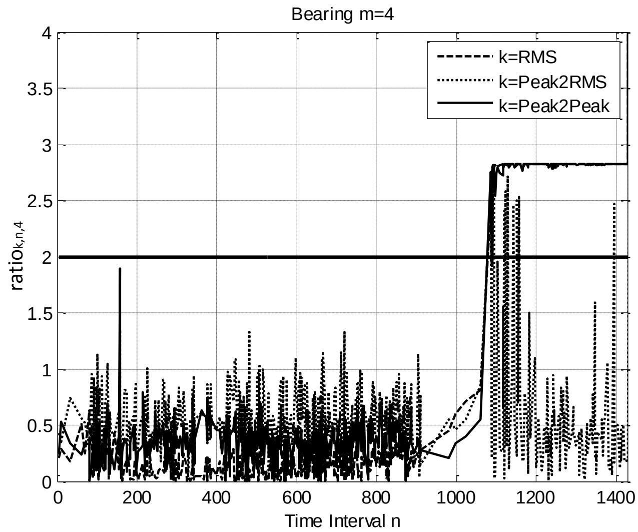

Fig. 5, Feature distribution ratio of bearing $m=4$.

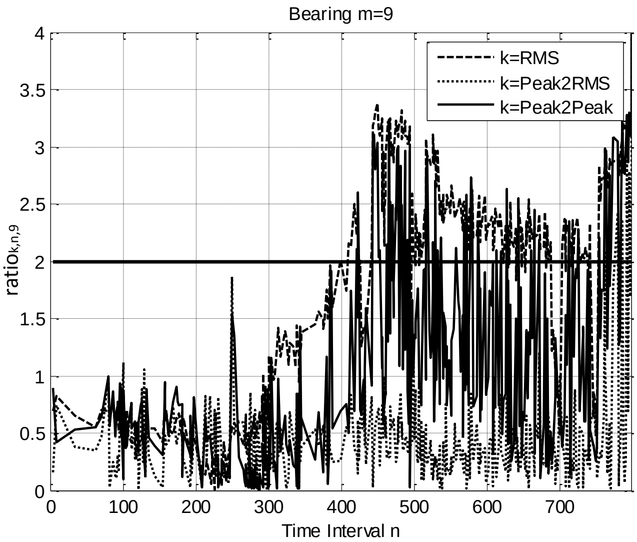

Fig. 6, Feature distribution ratio of bearing $m=9$.

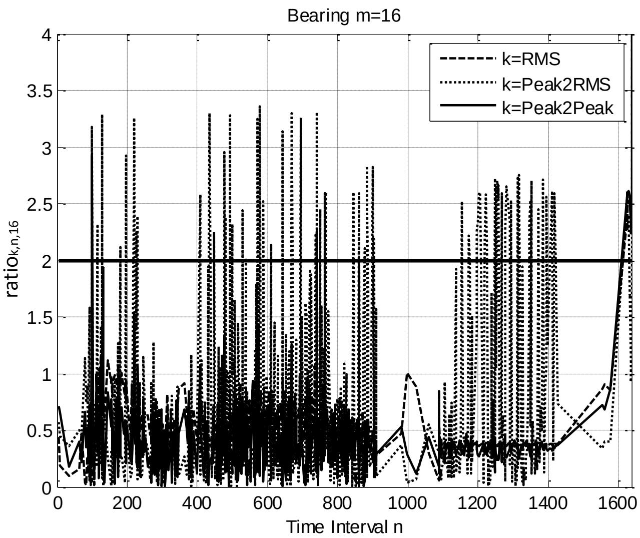

Fig. 7, Feature distribution ratio of bearing $m=16$.

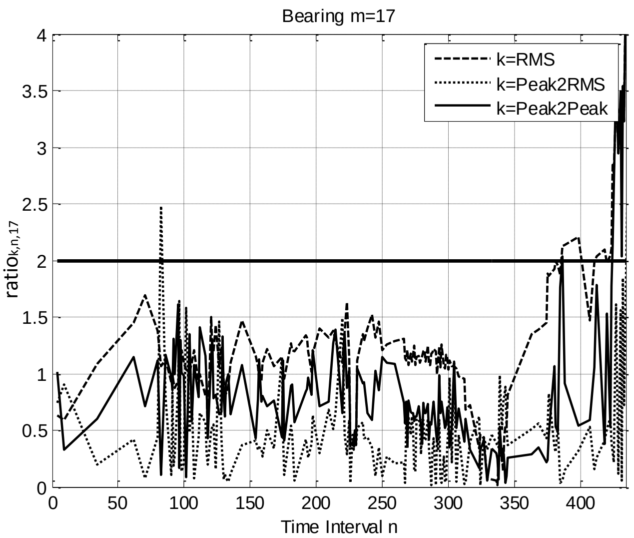

Fig. 8, Feature distribution ratio of bearing *m=17*.

Discussion

It can be seen that for all normal distributed bearings an unusual behavior before the end of life time could be classified using no design specific quantitative thresholds. Bearing *m=2, 8,* and *16* show a very early detection of fewer than *6%* of the total bearing life time. An early classification is not a desired result because in this early state of the total life time of the bearing the behavior should be still considered as usual behavior. By comparing the early detection of bearing *m=16* with Fig. 7 it can be seen that this is due to noisy Peak2RMS and Peak2Peak features. It also can be seen that at the end of the bearing life time a usual behavior was also classified. Therefore further investigations should be done to lower the impact of noisy features. This fact shows the dependency of selected features of the method.

TABLE 2: SUMMARIZED RESULTS FOR ALL 17 BEARINGS.

Bearing m	**Nb. of measured intervals n**	**Nb. of normal distributed intervals**	**Interval of fist unusual behavior**	**Percentage of life time**
1	2803	620	-	-
2	871	444	6	1
3	2375	620	-	-
4	1428	607	1087	76
5	2463	620	-	-
6	2448	620	-	-
7	2259	620	-	-
8	911	470	34	4
9	797	399	420	53
10	1955	657	-	-
11	751	370	745	99
12	2311	620	-	-
13	701	337	693	99
14	230	70	104	45
15	515	221	491	95
16	1637	620	100	6
17	434	165	386	89

V. CONCLUSION

In this paper a method for fleet monitoring is given to detect unusual machine behavior of a single machine if compared to the fleet. The method is applied to vibration data of *17* bearings. For a fleet size of at least 8 bearings, for every bearing in this fleet unusual behavior could be detected before the end of the bearing life time. The results show the detectability depending on fleet size and feature selection. Further research regarding a sensitivity analyses, feature extraction and feature interconnectivity is needed.

REFERENCES

[1] Rieg Frank, S. R. (2012). *Handbuch Konstruktion* . Hanser

[2] Voith, G. (April 08, 2014). *Voith*. Retrieved May 06, 2014 from: http://voith.com/de/index.html

[3] C.A. Douglas, G.P. Harrison, J.P. Chick "Life cycle assessment of the Seagen marine current turbine", Proc. IMEchE Vol. 222 Part M, 2008,DOI: 10.1243/1475 0902JEME94

[4] IEEE® Standard on Transitions, Pulses, and Related Waveforms, IEEE Standard 181, 2003.

[5] R.B. D'Agostino (1986). "Tests for the Normal Distribution". In D'Agostino, R.B. and Stephens, M.A. Goodness-of-Fit Techniques. New York: Marcel Dekker. ISBN 0-8247-7487-6.

[6] A. Gut (2009) An Intermediate Course in Probability, Springer. ISBN 9781441901613

[7] P. Nectoux, R. Gouriveau, K. Medjaher, E. Ramasso, B. Morello, N. Zerhouni, C. Varnier. "PRONOSTIA: An Experimental Platform for Bearings Accelerated Life Test", *IEEE International Conference on Prognostics and Health Management*, Denver, Colorado, USA, 2012.

